



MARMARA UNIVERSITY
INSTITUTE FOR GRADUATE STUDIES
IN PURE AND APPLIED SCIENCES



**APPLYING FORECASTING METHODS TO REDUCE
THE COST OF SPARE PARTS INVENTORY IN A
CONSTRUCTION EQUIPMENT COMPANY**

ALPER SADIK TAVUKÇU

MASTER THESIS

Department of Industrial Engineering

Thesis Supervisor

Prof. Dr. Bahar Sennaroğlu

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ÖZET

YEDEK PARÇA ENVANTER MALİYETİNİ AZALTMAK İÇİN TAHMİN YÖNTEMLERİNİN BİR İŞ MAKİNESİ SATICISI FİRMADA UYGULANMASI

Otomobil, iş makinesi, uçak, beyaz eşya, elektronik cihaz üreticileri hem üretim adetleri bakımından hem de ciro anlamında dünyanın en büyük endüstriyel şirketlerdir. McKinsey tarafından 2015 yılı verileri kullanılarak yapılan ve 2017 yılında yayınlanan bir rapor, sadece otomotiv endüstrisinde dünya çapında yapılan işçilik ve yedek parça satışlarının tutarının 760 milyar dolara ulaştığını ortaya koymuştur. Bu tutarın yarısından fazlası yedek parça satışlarından elde edilmiştir.

Yedek parça envanter maliyetinde yapılacak en ufak bir iyileştirme, firmalara önemli oranda mali açıdan fayda sağlayacağı gibi müşteri memnuniyetini artırıcı etkisi de olacaktır. Bu çalışmada, on bin kalemi stoklu yaklaşık elli bin kalem yedek parça envanter kaydına sahip bir iş makinesi satıcı firmasının stok maliyetinin azaltılması ve müşteri memnuniyetinin artırılması amaçlanmaktadır. Çalışma konusu olan iş makinesi firması, hâlihazırda yedek parça stok siparişlerini sabit periyotlarla değişken talep verisinin 12 aylık hareketli ortalamasını kullanarak hazırlamaktadır. Firmanın talep tahmini için kullandığı hareketli ortalama yönteminin en az stok maliyetini ve en çok müşteri memnuniyetini sağlayan yöntem olup olmadığı araştırılmıştır.

Bu çalışmada, firmanın 36 aylık yedek parça satış rakamları farklı istatistiksel talep tahmin yöntemleriyle analiz edilmiş mevcut yöntemden daha fazla fayda sağlayan yöntem tespit edilmiştir. Binlerce yedek parça kalemini en iyi temsil eden bir örnek grubu seçilmiştir. 36 aylık periyot içinden bir test periyodu belirlenmiş ve farklı talep tahminleri yöntemleri bu örnek yedek parça grubunun talep tahminleri için kullanılmıştır. Her bir tahmin yönteminin yol açtığı stok tutma maliyeti ve kayıp satış maliyeti hesaplanmış ve mevcut talep tahmin yönteminden daha az maliyet sağlayan yöntem tespit edilmiştir.

ANAHTAR SÖZCÜKLER: Yedek Parça, Envanter, Maliyet, Talep Tahmini, Tedarik.

ABSTRACT

APPLYING FORECASTING METHODS TO REDUCE THE COST OF SPARE PARTS INVENTORY IN A CONSTRUCTION EQUIPMENT COMPANY

Car, construction equipment, aircraft, white goods and electronic appliances manufacturers are the largest industrial companies in the world in terms of production amounts and turnover. A report published by McKinsey in 2017 shown that labor and spare parts turnover reached 760 billion USD in 2015 around the world. More than half of this amount was obtained from spare parts sales.

Any improvement on inventory cost provides financial benefits to companies and also increases customer satisfaction. In this study, it is aimed to reduce the cost of inventory of a construction equipment vendor with spare parts stock of ten thousand available out of almost fifty thousand registered items and increase customer satisfaction. The vendor company prepares spare part orders by using 12-month moving average of variable demand data. The research question was whether or not moving average method used by the company provides minimum cost and maximum customer satisfaction.

In this study, 36-month spare parts sales data was analyzed by using various forecasting methods and the method giving the best results was determined. A sample group that best represents thousands of spare parts was selected for the analysis. A test period was picked out of 36-month time period and various forecasting methods were used for demand forecasting of this sample group. Stock on hand amount and lost sales amount was calculated for each demand forecast method and the method which provides minimum cost was determined.

KEY WORDS: Spare Parts, Inventory, Cost, Demand Forecast, Supply.

SYMBOLS

α : Smoothing parameter for the level between 0 and 1

β : Smoothing parameter for the trend between 0 and 1

γ : Smoothing parameter for the season between 0 and 1

r_k : Autocorrelation coefficient at lag k

Y_t : Actual observation for time period t

F_t : Forecast value for time period t

e_t : The error term at time period t

ABBREVIATIONS

ACF	: Autocorrelation Function
AIC	: Akaike's Information Criterion
ANN	: Artificial Neural Networks
AR	: Autoregressive
ARMA	: Autoregressive Moving Average
ARIMA	: Autoregressive Integrated Moving Average
BPNN	: Back Propagation Neural Network
MA	: Moving Average
MAE	: Mean Absolute Error
MSE	: Mean Squared Error
MAPE	: Mean Absolute Percentage Error
MPE	: Mean Percentage Error
OF	: Objective Function
PACF	: Partial Autocorrelation Function
PE	: Percentage Error
RMSE	: Root Mean Squared Error
SES	: Simple Exponential Smoothing
SKU	: Stock Keeping Unit

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1. INTRODUCTION

Industrial products such as cars, construction equipments, airplanes, white goods are manufactured by combining thousands of parts. These products can fail after sales, during the use of customer. Customer requests repair for their broken products from producer or seller. Company fixes product by replacing broken part if it is needed after technical inspection. Spare part described as “the new part to be replaced for malfunctioned part of a machine” by Turk Dil Kurumu. Broken part is replaced for free if product is under warranty. Company charges customer for new part, if warranty of product is expired. Therefore, company supplies spare part for warranty liabilities and also to get some profit from sales.

Companies try to supply spare parts within shortest time and with lowest cost for demand coming from customer, either to meet warranty liabilities or to get profit. Producer procures components of products from different suppliers. Therefore, producer or seller of product has to keep some spare parts inventory just in case any delay or problem in supply chain. Activities such as storing, stock control, inventory cost calculation, delivery or receiving goods are called inventory management. Supply chain is defined as a structure which been added suppliers, logistics service providers and sales channels to inventory management. Managing whole supply chain processes is called supply chain management (Kopczak, 1997).

The most important step of spare parts inventory management is to check stock level periodically and to procure spare parts decreased due to customer demand. Person in charge of inventory procurement encounters some important questions such as what the optimum stock level should be, in which level, procurement of a stock item will be done or what order quantity will be.

Main objective for a person who is in charge of inventory control is to keep inventory cost lower while providing best service to beneficiaries. There are advantages or disadvantages of low inventory level or high inventory level. Stored items can be exhausted before than expected time due to low inventory level. This can cause lost sale and customer dissatisfaction. On the other hand, high inventory level can cause stock holding cost and be negative effect on cash flow of company because of excessive investment to inventory (Ozturk, 1994).

Car, construction equipment, aircraft, white goods and electronic appliances manufacturers are the largest industrial companies in the world in terms of production amounts and turnover. A report published by McKinsey in 2017 shown that labor and spare parts turnover reached 760 billion US dollars in 2015 around the world (McKinsey, 2017). More than half of this amount was obtained from spare parts sales. Having considered other industries, spare parts sales and inventory amounts reached significant level globally. Any improvement on inventory cost provides financial benefits to companies and also increases customer satisfaction.

Failure time of a part and spare part demand time are totally uncertain. Therefore, customer demand and inventory consumption speed are variable. Uncertainty and variability are very big problem for procurement specialists. Procurement specialists try to forecast future sales and demand amount of a stock item by analyzing historical sales and demand data. Diminished stock items are ordered from suppliers by using forecast results and considering lead time.

There are various mathematical methods to analyze historical data and to forecast future values. Every method has weak and strong sides. Also, different methods can cause different forecasting results for the same data set. Each forecasting result will have an effect on supply process. In this study, it is aimed to reduce the cost of inventory of a construction equipment vendor with spare parts stock of ten thousand available out of almost fifty thousand registered items and increase customer satisfaction.

There are many forecasting methods in literature. Quantitative forecasting techniques are classified into two; time series and explanatory models. While time series forecasting methods consider historical data of one variable, the variable to be forecasted has a linear or non-linear relationship with one or more independent variables in explanatory models. As the long-term historical data of a variable is examined, four different patterns are observed: horizontal, cyclical, and seasonal and trend. There are various time series forecasting methods. These are relatively intermediate methods such as moving average methods, exponential smoothing methods, exponential smoothing with trend adjustment and advanced methods such as autoregressive ARIMA models (Makridakis et al., 1998).

The construction equipment vendor which is subject of this study prepares spare part orders based on 12-month moving average of variable demand data. It was researched that if moving average method used by company provides minimum cost and maximum customer satisfaction or not.

A sample group that best represents thousands of spare parts was selected. Sample group consists of three spare parts containing top selling first fifty parts which make up 38% of total sales. 36 months spare parts sales data was analyzed and seasonal pattern observed for these three parts. Last 12 months was picked as test period out of 36 months. Holt-Winters' and ARIMA methods were used for demand forecasting of this sample group. Stock on hand amount and lost sales amount was calculated for each demand forecast method and compared with current forecasting method in use and the method which provides minimum cost was determined.

2. FORECASTING METHODS

2.1. Introduction

The presence of dynamic and uncertain economic environments and the need to control some key variables for the survival caused ever greater attention towards forecasting techniques by companies. Forecasting methods are part of decision-making activities. Some of the fields where forecasting actually plays a key role (Makridakis et al, 1998):

1. Scheduling: Forecasting provides better scheduling for transportation, production, money management, human resources etc. Demand forecasts of product, labor, finance or service are main input for scheduling.
2. Acquiring resources: Forecasting is needed for future resource requirements such as raw material supply, hiring personnel, and equipment or machinery requirements.
3. Determining resource requirements: Organizations should do long term resources planning. Market opportunities, environmental factors, financial status, human, product, and technological resources have an impact on long term decisions. This process requires good forecasts and executives who can make good inference by using predictions.

To deal with uncertain and dynamic environment many forecasting techniques have been developed. These forecasting techniques are classified into two groups; qualitative techniques and quantitative techniques. If there is not enough data on relevant subject, qualitative techniques must be used. If there is numerical historical data for researched subject and also if these data shows certain pattern to predict future values then quantitative techniques must be used (Hyndman & Athanasopoulos, 2018).

Qualitative methods are executives' opinions, market research, sales team estimations and the Delphi method. Quantitative forecasting techniques are classified into two; time series and explanatory models. While time series forecasting methods consider historical data of one variable, the variable to be forecasted has a linear or non-linear relationship with one or more independent variables in explanatory models. Due to 36 months spare parts historical sales data of construction equipment company is available, time series forecasting methods were used in this study.

2.2. Time Series Methods

The aim of time series forecasting methods is to determine the pattern in the historical data series. Finding out type of data pattern is a key point to obtain most suitable forecasting method. Graphs are very effective way to observe pattern on past data. Time plot is the ideal graph type. As the long-term historical data of a variable is examined, four different patterns are observed: horizontal, trend, seasonal and cyclical.

- Horizontal pattern: the data values fluctuate around a constant mean.
- Trend pattern: long-term increase or decrease in the data creates trend pattern.
- Seasonal pattern: if historical data set is affected by seasonal factors such as months of the year, days of the month, days of the week then seasonal pattern is considered.
- Cyclical pattern: if historical data set shows irregular increases and decreases or unseasonal distribution then cyclical pattern occurs.

Figure 2.1 shows different time series patterns.

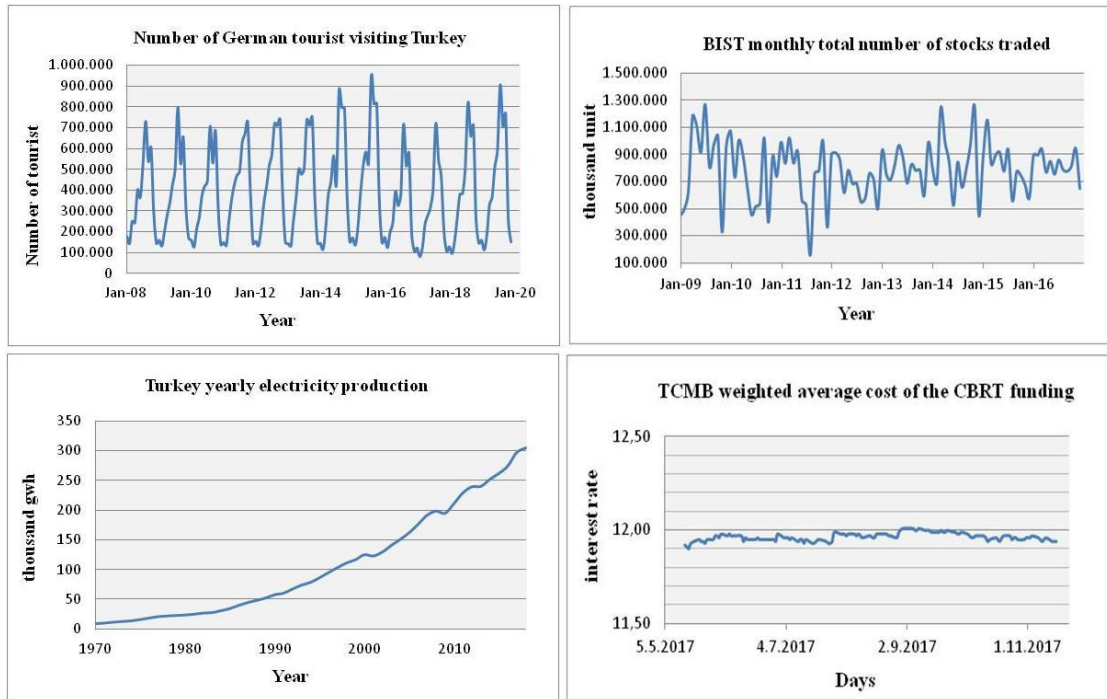


Figure 2.1 Examples of time series for different patterns. (Source: TCMB & TUIK)

Seasonal pattern can also be seen in two forms: additive and multiplicative. Multiplicative seasonality means that values of independent variable exponentially increase or decrease from season to season. Additive seasonality is described as linear increase or decrease in values of independent variable from season to season. Determining seasonal patterns is one of the very important steps of forecasting method selection process. Pegel classified additive and multiplicative seasonality in 1969. Figure 2.2 shows his classification.

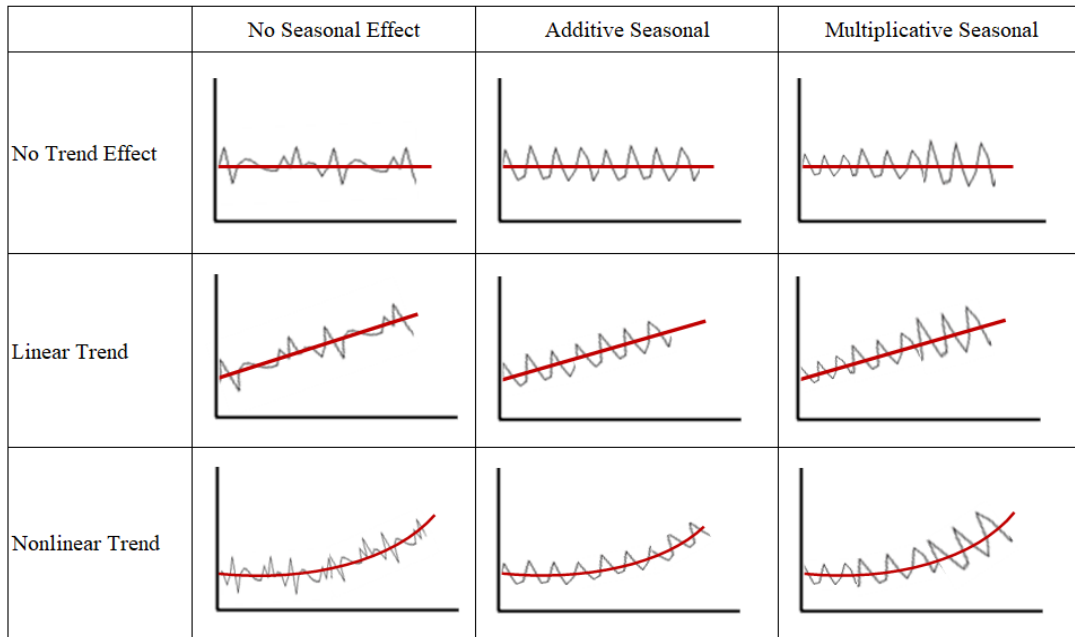


Figure 2.2 Patterns based on Pegels' (1969) classification

Beside graphical visualization of historical data to analyze patterns, a numerical statistic is also used which is named autocorrelation. Correlation measures the extent of a linear relationship between two variables; autocorrelation measures the linear relationship between lagged values of a time series (Hyndman and Athanasopoulos, 2018). For example, r_1 measures the relationship between y_t and y_{t-1} , r_2 measures the relationship between y_t and y_{t-2} , and so on.

The value of r_k can be written as

$$r_k = \frac{\sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^T (y_t - \bar{y})^2} \quad (2.1)$$

where T is the length of the time series.

After calculation of r_k values, a plot is drawn. This plot shows the autocorrelation function or ACF. The plot is also named as a correlogram. If there is a trend on data, ACF has a tendency to be large and positive for small lags. However, as the lags increase, positive values of ACF slowly decrease. The autocorrelations are larger for the seasonal lags (at multiples of the seasonal frequency) than for other lags. When data has trend and seasonal pattern at the same time, ACF reflects both characteristic on the plot. The number of German tourist visiting to Turkey series plotted in Figure 2.3 shows seasonal patterns.

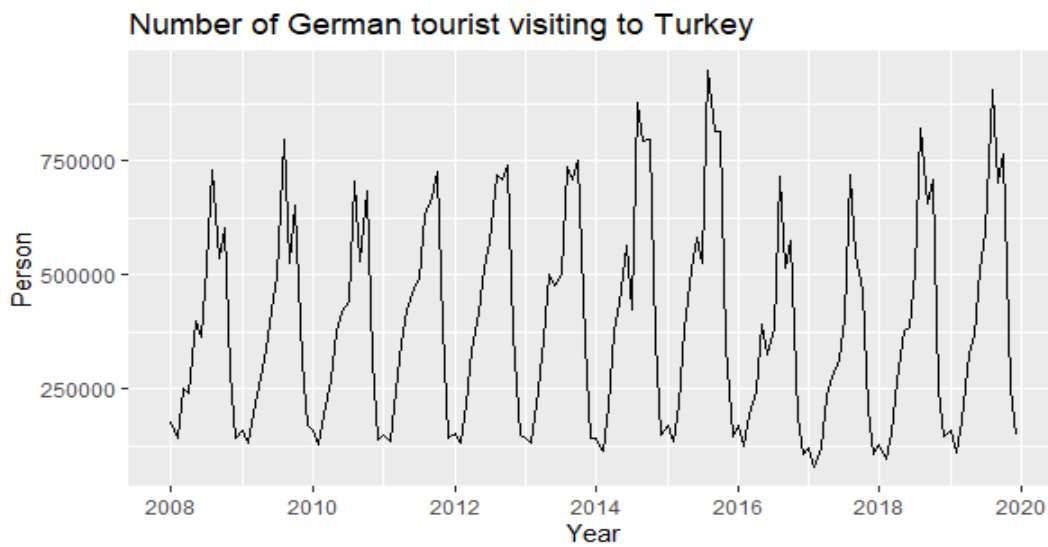


Figure 2.3 The number of German tourist visiting to Turkey (Source: TUIK)

Its ACF plot is shown in Figure 2.4

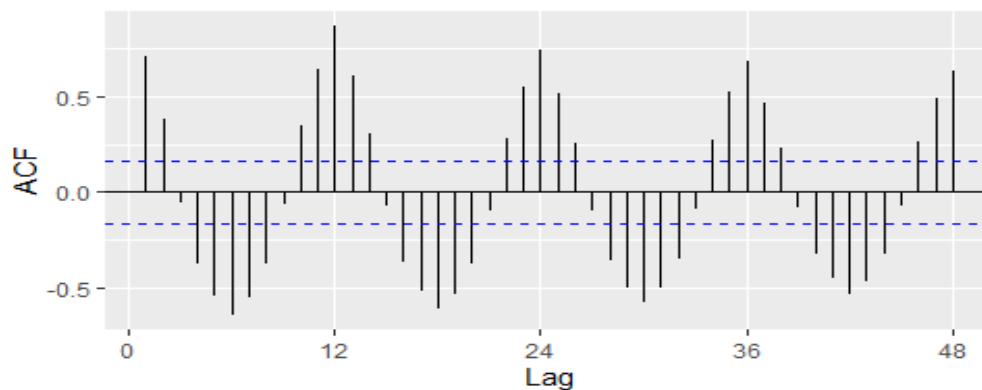


Figure 2.4 ACF plot of the number of German tourist visiting to Turkey

Spikes in 12th, 24th, 36th and 48th lags show seasonal pattern on time series data. Decreasing correlation coefficients between lags 12th and 48th indicates trend pattern.

2.2.1. Moving average method

Moving average is calculated by dividing the total of past values of a variable by the determined past time interval. The oldest data is leaved out from the moving average calculation and most recent data is included. Thus, forecast for the next period is obtained. The number of data points in each average remains constant and includes the most recent observations (Makridakis et al., 1998).

A moving average forecast of order k, or MA (k), is given by

$$F_{t+1} = \frac{1}{k} \sum_{i=t-k+1}^t Y_i \quad (2.2)$$

2.2.2. Holt-Winters' method

Winters (1960) improved Holt's method to obtain seasonality. Holt's method only considers trend pattern on data set. Therefore, Winters added seasonality calculations to Holt's method. There are two Holt-Winters' methods which are an additive or multiplicative way based seasonality pattern. If values of independent variable exponentially increase or decrease from season to season, multiplicative method is used. If there is a linear increase or decrease in values of independent variable from season to season, additive method is used.

The fundamental equations of Holt-Winters' multiplicative method are

$$\text{Level: } L_t = \alpha \frac{Y_t}{S_{t-s}} + (1 - \alpha)(L_{t-1} + b_{t-1}) \quad (2.3)$$

$$\text{Trend: } b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1} \quad (2.4)$$

$$\text{Seasonal: } S_t = \gamma \frac{Y_t}{L_t} + (1 - \gamma)S_{t-s} \quad (2.5)$$

$$\text{Forecast: } F_{t+m} = (L_t + b_t m)S_{t-s+m} \quad (2.6)$$

L_t : The level of the series

S : The length of seasonality (e.g., number of months or quarters in a year)

b_t : The trend

F_{t+m} : The forecast form periods ahead

α : Smoothing parameter for the level between 0 and 1

β : Smoothing parameter for the trend between 0 and 1

γ : Smoothing parameter for the season between 0 and 1

To initialize the multiplicative Holt-Winters' method, initial values of the level L_t , the trend b_t , and the seasonal indices S_t should be calculated. At least one complete season's data set (i.e., s periods) should be used to obtain initial values of the seasonal indices. Initial value of the level is calculated by getting the average of the first season:

$$L_s = \frac{1}{s} (Y_1 + Y_2 + \dots + Y_s) \quad (2.7)$$

Two complete seasons (i.e., $2s$ periods) should be used to obtain initial values of the trend as follows:

$$b_s = \frac{1}{s} \left[\frac{Y_{s+1} - Y_1}{s} + \frac{Y_{s+2} - Y_2}{s} + \dots + \frac{Y_{s+s} - Y_s}{s} \right] \quad (2.8)$$

At last, the seasonal indices are initialized using the ratio of the first few data values to the mean of the first year:

$$S_1 = \frac{Y_1}{L_s}, \quad S_2 = \frac{Y_2}{L_s}, \quad \dots \quad S_s = \frac{Y_s}{L_s}$$

The equations for Holt-Winters' additive method:

$$\text{Level: } L_t = \alpha(Y_t - S_{t-s}) + (1 - \alpha)(L_{t-1} + b_{t-1}) \quad (2.9)$$

$$\text{Trend: } b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1} \quad (2.10)$$

$$\text{Seasonal: } S_t = \gamma(Y_t - L_t) + (1 - \gamma)S_{t-s} \quad (2.11)$$

$$\text{Forecast: } F_{t+m} = L_t + b_t m + S_{t-s+m} \quad (2.12)$$

2.2.3. The Box-Jenkins methodology for ARIMA models

Autoregressive - Integrated - Moving Average (ARIMA) models were frequently used by George Box and Gwilym Jenkins in the early 1970s (Box and Jenkins, 1968). Box-Jenkins modeling procedure consists of three phases: identification, estimation and testing and application.

Identification phase has basically two steps; data preparation and model selection. The aim of data preparation is transforming data to stabilize variance and differencing data to stabilize mean to obtain a stationary time series. Autocorrelation function (ACF) and partial autocorrelation function (PACF) are identified to see potential models. Estimation and testing stages consist of estimation and diagnostics steps. In estimation step, parameters are estimated for potential models and suitable criterion is selected for best model. Estimation and testing stage contain some diagnostic measures. ACF and PACF of residuals should be checked, portmanteau test of residuals should be applied and white noise inspection for residuals should be done. If the test results are within the limits, chosen model can be used for forecasting. If test results are not appropriate, a new model should be used. Figure 2.5 shows flow of The Box-Jenkins Methodology.

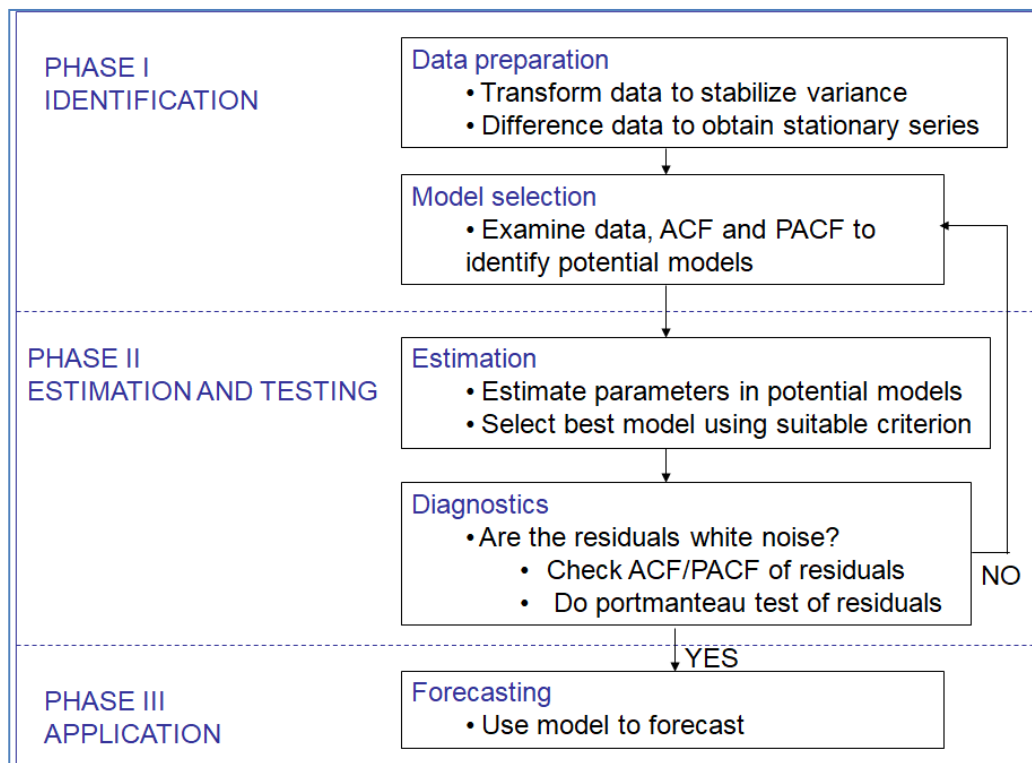


Figure 2.5 Flow of The Box-Jenkins Methodology (Makridakis et al., 1998)

2.2.3.1. Stationarity

Stationarity means that there is no extreme increase or extreme decrease in the data. The values should be almost horizontal throughout the time axis. The data rises and falls around a constant mean, and the variance of the fluctuation stays stable. Using a time plot, examining ACF and PACF and using statistical tests (unit root tests) are best ways to identify stationarity on a time series. If there is no sign of a change in the mean over time, it is considered that the series is stationary in the mean. If there is no significant change in the variance, it is considered that the series is stationary in the variance. The autocorrelations of stationary data reach to zero within closer lags, while the autocorrelations of non-stationary series are different from zero for several time lags. The autocorrelations of non-stationary data decline gradually as the number of time lags increases. In general, the autocorrelation at lag k (r_k) for non-stationary data will be relatively large and positive, until k gets big enough; the random error components begin to dominate the autocorrelation. Slow decrease in the size of the autocorrelations on the ACF of non-stationary data is observed when the number of time lags increases. A sharp spike is seen close to 1 at lag 1 on the PACF of non-stationary data (Makridakis et al, 1998).

The partial autocorrelation coefficient of order k is denoted by α_k and can be calculated by regressing Y_t against $Y_{t-1} \dots Y_{t-k}$. The partial autocorrelation α_k is the estimated coefficient b_k from this multiple regression ($\hat{\alpha}_k = b_k$)

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \dots + b_k Y_{t-k} \quad (2.13)$$

Differencing is the best method to eliminate non-stationarity in the mean. The difference is taken between actual observation and previous observation.

$$Y'_t = Y_t - Y_{t-1} \quad (2.14)$$

Sometimes, differencing is not enough to remove non-stationarity from the original data set. A second differencing should be needed if the first differenced values are still non-stationary.

$$Y''_t = Y'_t - Y'_{t-1} \quad (2.15)$$

If original time series has seasonal pattern, seasonal differencing should be appropriate.

$$Y'_t = Y_t - Y_{t-s} \quad (2.16)$$

Number of season period s will be 4 for quarterly data and 12 for monthly data. Seasonal differencing should be done before first differencing.

Besides differencing, another useful method is using backward shift operator. Backward shift operator (B) is simply a numeric factor which builds a mathematical relation between actual observation and past observations.

To shift the data back one period;

$$BY_t = Y_{t-1} \quad (2.17)$$

To shift the data back two periods;

$$B(BY_t) = B^2Y_t = Y_{t-2} \quad (2.18)$$

To shift the data back same month last year for monthly data;

$$B^{12}Y_t = Y_{t-12} \quad (2.19)$$

2.2.3.2. Models and model selection

Model selection is another key step of The Box-Jenkins Methodology. To determine the model, the appropriate order of a time series model should be considered. There are four main model types; autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA).

The general non-seasonal model is explained as ARIMA (p, d, q)

AR: p = order of the autoregressive part

I: d = degree of first differencing involved

MA: q = order of the moving average part

ARIMA(0,0,0) is considered as white noise model. Because, white noise model has no autocorrelation (Y_t does not depend on Y_{t-1}), no differencing and no moving average part (Y_t does not depend on e_{t-1}). ARIMA(0,1,0) is known as random walk model.

Because, random walk model has no autocorrelation (Y_t does not depend on Y_{t-1}) and no moving average part (Y_t does not depend on e_{t-1}) and has only one differencing.

Autoregressive model of order p , AR(p) is defined as;

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + e_t \quad (2.20)$$

c : constant term

ϕ_j : j th autoregressive parameter

e_t : the error term at time t

There are some restrictions on estimation of parameters. For AR(1) model ϕ_1 should be between -1 and 1 ($-1 < \phi_1 < 1$). For AR(2) model; $-1 < \phi_2 < 1$, $\phi_1 + \phi_2 < 1$, $\phi_2 - \phi_1 < 1$.

Moving average model of order q , MA(q) is defined as;

$$Y_t = c + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \quad (2.21)$$

c : constant term

θ_j : j th autoregressive parameter

e_t : the error term at time t

Restriction on estimation of parameters for MA(1) model is $-1 < \theta_1 < 1$ and for MA(2) model are $-1 < \theta_2 < 1$, $\theta_2 + \theta_1 > -1$, $\theta_1 - \theta_2 < 1$.

ARMA($p, 0, q$) model is combination of AR(p) and MA(q) and defined as;

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \quad (2.22)$$

However, ARMA model is used if data is stationary

White noise model is used if there is no correlation from period to period. Observation Y_t contains two parts; a random error component e_t and level c .

$$Y_t = c + e_t \quad (2.23)$$

Forecast errors should have a white noise model. White noise model indicates that there is no pattern on errors and errors are randomly distributed. If the errors still contain pattern after forecasting, the forecasting model should be revised.

ARIMA(0,1,0) is called as random walk model. Random walk model includes previous observation and error which has white noise.

$$Y_t = Y_{t-1} + e_t \quad (2.24)$$

The general seasonal model is shown as ARIMA (p, d, q)(P,D,Q)_s

(p, d, q) : non-seasonal part of the model

(P,D,Q)_s : seasonal part of the model

p and P : order of the autoregressive part

d and D : degree of differencing involved

q and Q : order of the moving average part

s : the length of seasonality

Seasonality of in the time series data can be observed by significant autocorrelation at the seasonal lags in the PACF and ACF. For instance, in the ACF, yearly seasonality makes spike at 12th lag. The PACF indicates exponential decrease at lags 12, 24, and 36.

Calculations are rather simple; however, notations can be complex for seasonal ARIMA models. As an example, quarterly ARIMA(1,1,1)(1,1,1)₄ formulated as follows;

$$(1 - \phi_1 B)(1 - \Phi_1 B^4)(1 - B)(1 - B^4)Y_t = (1 - \theta_1 B)(1 - \Theta_1 B^4)e_t \quad (2.25)$$

Parts of the model equation are;

$(1 - \phi_1 B)$	Non-seasonal AR(1)
$(1 - \Phi_1 B^4)$	Seasonal AR(1)
$(1 - B)$	Non-seasonal difference
$(1 - B^4)$	Seasonal difference
$(1 - \theta_1 B)$	Non-seasonal MA(1)
$(1 - \Theta_1 B^4)$	Seasonal MA(1)

Breakdown of seasonal ARIMA(1,1,1)(1,1,1)₄ model is;

$$\begin{aligned} Y_t = & (1 + \phi_1)Y_{t-1} - \phi_1 Y_{t-2} + (1 + \Phi_1)Y_{t-4} - (1 + \phi_1 + \Phi_1 + \phi_1 \Phi_1)Y_{t-5} \\ & + (\phi_1 + \phi_1 \Phi_1)Y_{t-6} - \Phi_1 Y_{t-8} + (\Phi_1 + \phi_1 \Phi_1)Y_{t-9} - \phi_1 \Phi_1 Y_{t-10} \\ & + e_t - \theta_1 e_{t-1} - \Theta_1 e_{t-4} + \theta_1 \Theta_1 e_{t-5} \end{aligned} \quad (2.26)$$

Partial autocorrelation function (PACF) and autocorrelation function (ACF) are very significant indicators for ARIMA model selection. Some certain ACF and PACF patterns give idea about which ARIMA model is most suitable for data set. Table 2.1 shows possible patterns in the ACF and PACF for simple AR and MA models.

Table 2.1 Expected patterns in the ACF and PACF for simple AR and MA models (Makridakis et al., 1998)

Process	ACF	PACF
AR(1)	Exponential decay: on positive side if $\phi_1 > 0$ and alternating in sign starting on negative side if $\phi_1 < 0$.	Spike at lag 1, then cuts off to zero: spike positive if $\phi_1 > 0$, negative if $\phi_1 < 0$.
AR(p)	Exponential decay or damped sine-wave. The exact pattern depends on the signs and sizes of $\phi_1, \dots, \phi_p$.	Spikes at lags 1 to p , then cuts off to zero.
MA(1)	Spike at lag 1 then cuts off to zero: spike positive if $\theta_1 < 0$, negative if $\theta_1 > 0$.	Exponential decay: on negative side if $\theta_1 > 0$ and alternating in sign starting on positive side if $\theta_1 < 0$.
MA(q)	Spikes at lags 1 to q , then cuts off to zero.	Exponential decay or damped sine-wave. The exact pattern depends on the signs and sizes of $\theta_1, \dots, \theta_q$.

Theoretical ACF and PACF example figures gives AR(1) and MA(1) impression to forecaster. First row of Figure 2.6 indicates AR(1) model and second row of figure 2.6 indicates MA(1) model.

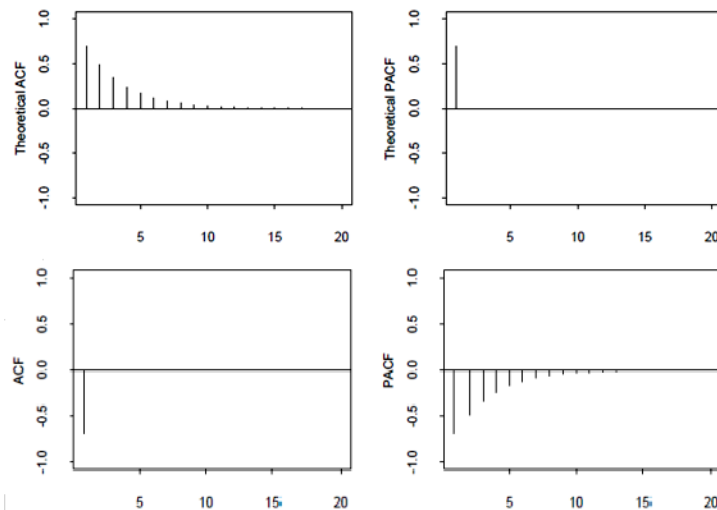


Figure 2.6 Theoretical ACF and PACF for an AR(1) and MA(1) model (Makridakis et al., 1998)

2.2.3.3. Estimation and testing

ACF and PACF values give an idea about AR and MA models. However, they are not adequate performance indicators for AR and MA combinations. Another performance measures are needed. To obtain the best ARIMA model, an order combination which gives the smallest sum of squared errors or the largest value for the likelihood should be chosen. Accepted as regression goodness of fit index R^2 can be improved by adding new explanatory variable to regression model. However, adding new terms in the regression models increases complexity and decreases understanding of the model. Solution for this dilemma is to penalize likelihood. Akaike's Information Criterion (AIC) is the widely used penalized likelihood procedure.

$$AIC = -2\ln L + 2r \quad (2.27)$$

The corrected AIC:

$$AICc = -2\ln L + 2r \frac{n}{n - r - 1} \quad (2.28)$$

$\ln$: the natural log

L : the likelihood of the data

n : the number of observations

r : the total number of parameter (including the constant term) in the ARIMA model

ARIMA model order parameters p, q, P, Q which minimize AIC value are chosen among different order combinations.

After AIC calculation and choosing ARIMA model which has minimum AIC value, still some diagnostic checking is needed. First of all, residuals should be examined if they have any pattern or not. If the residuals still contain pattern after model selection, the model should be revised. Also, ACF and PACF of the residuals should not show meaningful autocorrelations and meaningful partial autocorrelations. Also, portmanteau test can be applied on a set (h) of autocorrelation values (r_k) of residuals. Well known portmanteau test is Box-Pierce test that is based on the Box-Pierce Q statistic.

$$Q = n \sum_{k=1}^h r_k^2 \quad (2.29)$$

2.2.3.4. Forecasting with ARIMA models

Forecasting phase can start after model selection, parameter estimation and testing. First thing should be done is expand the model to obtain conventional regression equation. For example, regression equation of ARIMA(0, 1, 1)(0, 1, 1)₁₂ model will be;

$$Y_t = Y_{t-1} + Y_{t-12} - Y_{t-13} + e_t - \theta_1 e_{t-1} - \theta_1 e_{t-12} - \theta_1 \theta_1 e_{t-13} \quad (2.30)$$

To forecast one period ahead, regression equation will be for Y_{t+1} ;

$$Y_{t+1} = Y_t + Y_{t-11} - Y_{t-12} + e_{t+1} - \theta_1 e_t - \theta_1 e_{t-11} - \theta_1 \theta_1 e_{t-12} \quad (2.31)$$

The e_{t+1} term in the equation is unknown and should be taken as zero. Estimation coefficients θ_1 and Θ_1 will get their numeric values.

2.3. Forecasting Accuracy

There are many forecasting methods and each forecasting method can generate different results for the same data set. Data set can contain different patterns such as horizontal, cyclical, seasonal and trend. A forecasting method particular is chosen based on the time series patterns in the data. For example, Holt-Winters' method gives good results for seasonal patterns. Therefore, different forecasting methods should be used on the same data set and forecast results should be compared using some performance measures.

All accuracy measure calculations are based on error. There are two types of error; fitting errors and forecasting errors. Fitting errors computed when the model has been fitted to the known data. Forecasting errors calculated after the data for the forecast periods have become available. Figure 2.7 shows forecasting scenario (Makridakis et al., 1998).

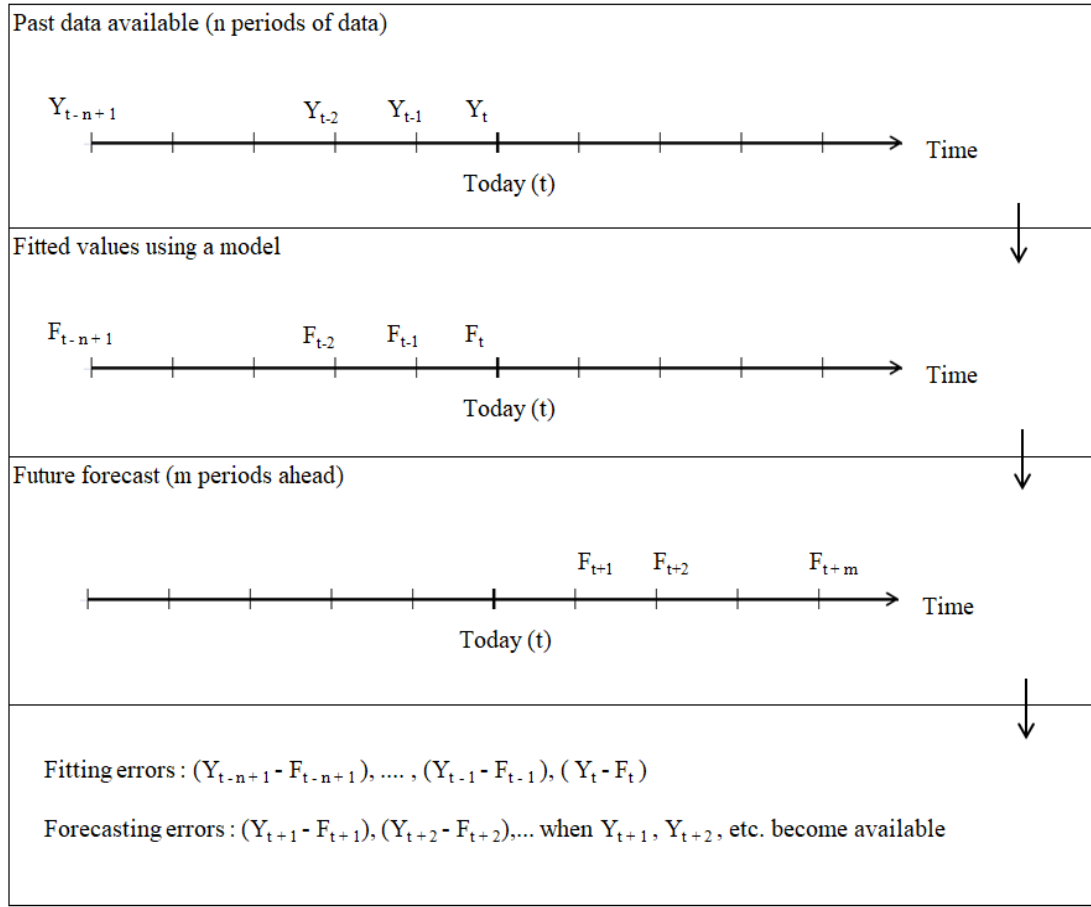


Figure 2.7 The forecasting scenario (Makridakis et al., 1998)

If Y_t is the actual observation for time period t and F_t is the forecast for the same period, then the error is defined as

$$e_t = Y_t - F_t \quad (2.32)$$

If observations and forecasts for n time periods are available, n errors can be obtained. When errors are obtained, forecasting accuracy measures based on the mean absolute error (MAE), the mean squared error (MSE), the root mean squared error (RMSE), percentage error (PE), the mean absolute percentage error (MAPE) and the mean percentage error (MPE) can be calculated;

$$MAE = \frac{1}{n} \sum_{t=1}^n |e_t| \quad (2.33)$$

$$\text{MSE} = \frac{1}{n} \sum_{t=1}^n e_t^2 \quad (2.34)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n e_t^2} \quad (2.35)$$

$$\text{PE} = \frac{Y_t - F_t}{Y_t} \times 100 \quad (2.36)$$

$$\text{MPE} = \frac{1}{n} \sum_{t=1}^n PE_t \quad (2.37)$$

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^n |PE_t| \quad (2.38)$$

3. FORECASTING METHODS APPLICATION IN A CASE STUDY

3.1. Literature Review

Mainly, basic time series methods such as moving average, simple exponential smoothing, Holt's method or Holt-Winter's method are used for spare parts demand forecasting.

However, some researchers studied on complex time series methods like Box-Jenkins method known as ARIMA. Businger and Read (1999) studied on US Navy spare parts inventory management. US Navy uses simple exponential smoothing method to make demand forecast. They proposed to US Navy three alternative ARIMA models; ARIMA(1,1,1), ARIMA(2,2,2) and ARIMA(3,2,3). Jiafu et al. (2009) used ARIMA to model spare parts demand for a factory. They built four different ARIMA models by using seven years historical data of four spare parts group. Vargas and Cortés (2017) did a comparative study of time series methods on automobile spare parts forecasting. They used ARIMA, ANN and ARIMA-ANNs hybrid methods for sample spare parts and compared forecasting accuracy for each simulation. Saravanan et al. (2019) used ARIMA method on a case study for spare part demand forecasting in an automotive company. The accuracy of the forecasting was improved by 40% from the current level.

Beside time series forecasting methods, explanatory data, failure data history and life data analyses were advised to be added to spare parts inventory calculations (Cavalieri et al., 2008). Nawzar and Sheik (2016) used multivariable regression and life data analysis to calculate spare parts demand forecasts. They also studied on a case study in Volvo Truck Company. Multivariable regression is based on big data such as population of main product, time of usage, mileage and runtime, service interval. Kim et al. (2017) studied on spare part demand forecasting for consumer goods using installed base information. They used multivariable regression model for spare part forecasting based on sales figures and sales region of main product. Chen et al. (2010) proposed a Regression-Bayesian-BPNN (Back Propagation Neural Network) method to obtain spare parts demand forecast. Compared with the classical ARMA models, Regression-Bayesian-BPNN showed higher accuracy.

Another challenge for spare parts demand forecasting is intermittent demand pattern. Croston (1972) proposed a forecasting method for intermittent demand. The method is

based on simple exponential smoothing (SES). Beside size of demand, the method also considers intervals between demand points.

Different empirical studies, simulations and case studies with real life data have also been used frequently. Porras and Dekker (2008) did an empirical study on an inventory control system for spare parts at a petrochemical refinery by using different forecasting methods. Bootstrapping was given best performance. Their method dropped inventory holding cost to 6.4%. Webby and O'Connor (1996) reviewed judgmental and statistical time series forecasting methods. They analyzed empirical studies and found out that statistical and judgmental forecasting techniques give best result when they combined together. Suyunova (2018) studied on spare parts demand forecasting simulations with different parameters by using Simple Moving Average and Simple Exponential Smoothing. Regon and Mesquita (2014) made a demand forecasting and inventory control simulation study on automotive spare parts. They used Simple Moving Average, Syntetos–Boylan Approximation and Bootstrapping methods. They suggested spare parts demand forecast and inventory simulations every 6 month with different methods due to demand pattern change over the time. Ozcift (2018) proposed Fuzzy Clustering Model for forecasting automotive spare part demands. Fuzzy modeling inference algorithm was used for modeling the system. Suggested model performed better in terms of forecasting accuracy.

Boylan et al. (2008) suggested demand categorization before spare parts demand forecasting. Different forecasting methods should be used on different stock keeping units (SKU's) based on demand categorization. They also did an empirical demand categorization study on automotive, aerospace and chemical industries data which supported by a UK based software company. Table 3.1 shows summary of literature review.

Table 3.1 Summary of literature review

Author	Title	Method	Result
Croston (1972)	Forecasting and Stock Control for Intermittent Demands	Method proposed by Croston	Croston proposed a method which considers intervals between demand incidences.
Webby & O'Connor (1996)	Judgemental and statistical time series forecasting: a review of the literature	Statistical and judgmental forecasting techniques	Statistical and judgmental forecasting techniques give best result when combined together.
Businger & Read (1999)	Identification of demand patterns for selective processing: a case study	Box-Jenkins (ARIMA)	The US Navy uses simple exponential smoothing to forecast spare parts demand. Authors suggest three different ARIMA models.
Porras & Dekker (2008)	An inventory control system for spare parts at a refinery: an empirical comparison of different re-order point methods	Bootstrapping approach	An empirical study was done in a petrochemical refinery by using different forecasting methods and bootstrapping was given best performance.
Cavalieri et al. (2008)	A decision-making framework for managing maintenance spare parts	Reliability based forecasting and time series based forecasting	Beside time series forecasting methods, failure data history and life data analysis should be added to calculations.
Boylan et al. (2008)	Classification for forecasting and stock control: a case study	Demand categorization	Different forecasting methods should be used for different SKU's based on demand categorization.
Jiafu et al. (2009)	The Forecasting Models for Spare Parts Based on ARMA	ARIMA	Authors built an ARIMA model for four spare parts in a real case study.

Table 3.1 Summary of literature review (continue)

Author	Title	Method	Result
Chen et al. (2010)	Aftermarket Demands Forecasting with a Regression-Bayesian-BPNN Model	Regression-Bayesian-BPNN	Compared with the classical ARMA models Regression-Bayesian-BPNN shows higher accuracy.
Regon & Mesquita (2014)	Demand forecasting and inventory control: A simulation study on automotive spare parts	Simple Moving Average, Syntetos–Boylan Approximation and Bootstrapping	Study suggests spare parts inventory simulations every 6 month with different methods.
Nawzar & Sheik (2016)	Improving Forecasting for the Aftermarket through Big Data A Case Study at Volvo Group	Multivariable regression and life data analysis	Spare parts future demand can be calculated by using multivariable regression and life data analysis. Big data has a potential for improving forecast accuracy.
Kim et al. (2017)	Spare part demand forecasting for consumer goods using installed base information	Installed base concepts Multivariable regression	Sales figures and sales region of main product should be used for spare part forecasting.
Vargas & Cortés (2017)	Automobile spare-parts forecasting: A comparative study of time series methods	ARIMA-ANNs hybrid	The mean absolute percentage error (MAPE) was reduced from an original 57% to 32.65%.
Suyunova (2018)	The Use of Demand Forecasting Techniques for the Improvement of Spare Part Management	Simple Moving Average and Simple Exponential Smoothing	Author studied on demand forecasting simulations with different parameters.
Ozcift (2018)	Fuzzy Clustering Model Proposal For Forecasting Automotive Spare Part Demands	Fuzzy Clustering Model	Fuzzy modelling inference algorithm is used for modelling the system. Suggested model performed better than other models.
Saravanan et al. (2019)	Forecasting Techniques for Sales of Spare Parts	ARIMA	The accuracy of the forecasting is improved by 40% from the current level.

3.2. Forecasting Methods Application in a Case Study

3.2.1. The company

This study examines demand forecasting methods' applications to reduce the cost of spare parts inventory in a construction equipment distributor company. The Company has been distributor of a Japanese construction equipment producer for almost 35 years in Turkey. Japanese producer manufactures construction equipments such as excavators, dozers, loaders, graders, trucks, forklifts etc. (Figure 3.1). The distributor company imports these equipments to Turkey and sells to constructors via its dealers or salesmen.



Figure 3.1 Construction equipment images

(Source of image: <https://pearlfradio.sx/wordpress/wp-content/uploads/2018/02/pic-heavy-equipment-2.jpg>)

Construction equipment can fail after sales, during the use of customer. Customer requests repair for their broken equipment from the company. The Company fixes product by replacing broken part if it is needed after technical inspection. Broken part is replaced for free if product is under warranty. The Company charges customer for new part, if warranty of product is expired. Therefore, company supplies spare part for warranty liabilities and also to get some profit from sales. The Company tries to supply spare parts, either to meet warranty liabilities or to get profit, within shortest time and with lowest cost for demand coming from customer.

The Company has 40 authorized service points in Turkey and one spare parts distribution center located in Gebze, Kocaeli. There are almost 50.000 SKU's registered inventories and approximately 10.000 of them are moving SKU's. The Company has only one supplier. Japanese producer has a spare parts distribution center in Belgium. The Company checks last 12-month sales figures and on hand stock every month, prepares spare parts orders by using 12-month moving average of demand and sends this spare parts order to Japanese producer's spare parts distribution center in Belgium. Spare parts distribution center in Belgium ships the spare parts order once in a month by truck. Order preparation, transportation and custom clearance takes almost 30 days which means lead time is approximately one month.

3.2.2. Spare parts order preparation

The Company does not order spare parts which are not sold more than five months in a year. For the rest, it calculates maximum stock level for each item every month. Order quantity is determined by subtracting on hand quantity from maximum stock level. Maximum stock level calculation is the most important part of the order preparation.

Chitale and Gupta (2014) explain periodic inventory review in their book. Periodic inventory review is called under different names such as P system of inventory control, fixed-order-interval system, fixed-order-period system or simply the periodic system (Figure 3.2). There are two types of periodic review; deterministic and probabilistic. Demand and lead time are known and relatively constant in deterministic review whereas demand and lead time fluctuate in probabilistic review. Spare parts demand is totally probabilistic and variable. Failure time of construction equipment and need for spare parts are uncertain and unpredictable. Therefore, maximum stock level is not stable depending on variable demand.

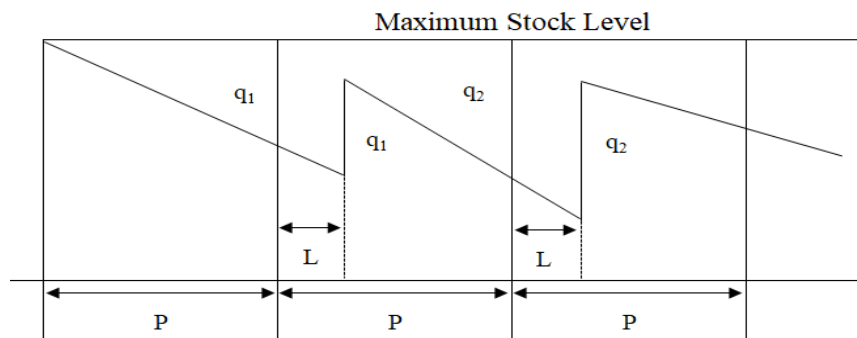


Figure 3.2 Periodic review system (Chitale & Gupta, 2014)

P = Review period

L = Lead time

q_1, q_2 = Order quantities

Maximum Stock Level (S) is obtained by considering safety stock, demand in review period and lead time. Maximum Stock Level (S) with 95% service level probability of demand is calculated with formula below;

$$S = R(P + L) + 1.65\sqrt{(P + L)} \sigma_D \quad (3.1)$$

R = Average consumption

P = Review period

L = Lead time

σ_D = Standard deviation of demand

However, the company has some constraints and some assumptions.

- The company is a distributor and has only one supplier which is main producer.
- Main producer accepts only one aggregated order for all spare parts items once in a month. Therefore, inventory review period is one month.
- Main producer makes only one shipment in a month. Therefore, lead time is fixed and it is one month.
- The company tolerates lost sales and does not keep any safety stock because of inventory investment requirement. Therefore, safety stock calculation is not added to maximum stock level calculation.

As an example, maximum stock level of SP1 for 26th month was obtained based on formula above. Demand value forecast was found 557 units by using moving average. Maximum stock level with no safety stock becomes;

$$S = R(P + L) = 557 (1+1) = 1114 \text{ units}$$

3.2.3. Demand categorization

Because spare parts demand is probabilistic and variable, some items are not sold in an inventory control period. Therefore, time series methods cannot be used for demand forecasting due to missing demand data. The Company does not order spare parts which are not sold more than five months in a year and for the rest, uses 12-month moving average method even demand data is missing.

Beside smooth demand, Boylan et al. (2008) studied on intermittent demand. Time series methods are not applicable for intermittent demand. Other approaches are needed such as intermittent demand based simple exponential smoothing proposed by Croston (1972). This study considers only smooth demand and time series forecasting methods.

3.2.4. Problem definition and data set preparation

The company prepares spare parts orders by using 12-month moving average of demand. However, it is uncertain that moving average method provides minimum on hand inventory and maximum customer satisfaction or not. Forecasting method should provide minimum on hand inventory amount and minimum lost sales amount.

Also, construction equipment is used in construction and mining business. Construction and mining business is highly related to weather conditions. Activity and working hours increase in good weather conditions. Therefore, seasonality is seen in spare parts sales.

If seasonality is the case, moving average method is not adequate for demand forecasting. Holt-Winters' method and ARIMA models provide more accurate forecasting results. Improvement in demand forecasting decreases on hand inventory amount and lost sales amount. Three spare parts from top selling first fifty parts with high inventory cost will be selected to represent whole inventory and to compare moving average method, which is used currently by the company, with Holt-Winters' and ARIMA methods. 36 months spare parts sales data will be analyzed and seasonal pattern will be observed for these three parts. Last 12 months will be picked as test period out of 36 months. Holt-Winters' and ARIMA methods will be used for demand forecasting of this sample group. Accuracy measures, stock on hand amount and lost sales amount will be calculated for each demand forecast method and compared with the current forecasting method in use and the method which provides maximum forecasting accuracy, minimum stock on hand amount and lost sales amount will be determined.

Top selling first fifty parts make up 38% of total sales. First spare part (SP1) is a filter with 40 Euro purchase price, second spare part is a bucket tooth (SP2) with 70 Euro purchase price and third spare part (SP3) is a pin with 50 Euro purchase price. Starting from January, 36 month demand data of these three parts is shown in Table 3.2.

Table 3.2 36 Months Demand Data of Selected Spare Parts

36 Months Demand Data of Selected Spare Parts			
	SP1	SP2	SP3
1	477	460	123
2	401	420	194
3	506	309	139
4	549	548	163
5	454	371	203
6	536	405	237
7	620	326	257
8	590	367	248
9	624	388	202
10	618	506	190
11	590	283	189
12	506	165	186
13	494	270	135
14	394	193	199
15	557	571	150
16	612	353	172
17	534	283	236
18	745	268	283
19	661	635	297
20	596	326	268
21	689	242	213
22	500	312	185
23	530	319	101
24	426	228	161
25	434	335	165
26	387	165	90
27	460	174	111
28	495	490	239
29	463	296	221
30	486	285	226
31	444	410	261
32	459	100	205
33	522	396	139
34	468	228	119
35	627	311	164
36	460	167	100

After spare parts selection and demand data collection, seasonal pattern will be investigated. Time plot (Figure 3.3) is very effective way to observe patterns on the data.

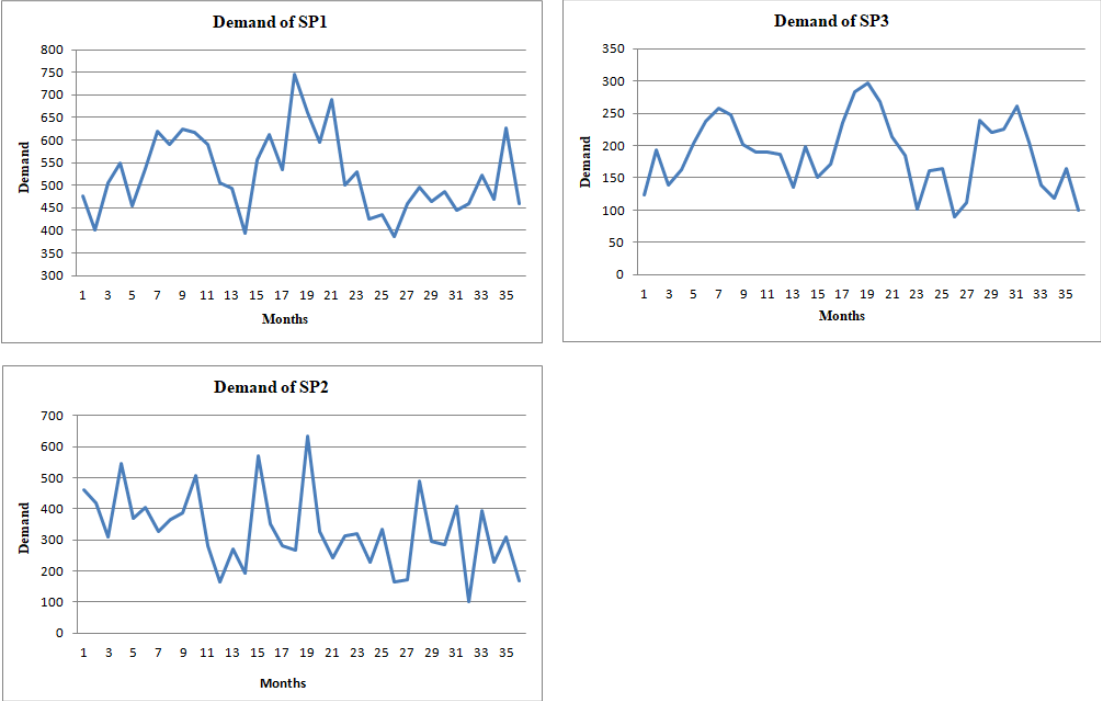


Figure 3.3 Time plots of three spare parts

Autocorrelation function (Figure 3.4) should also be used to analyze patterns in time series data.

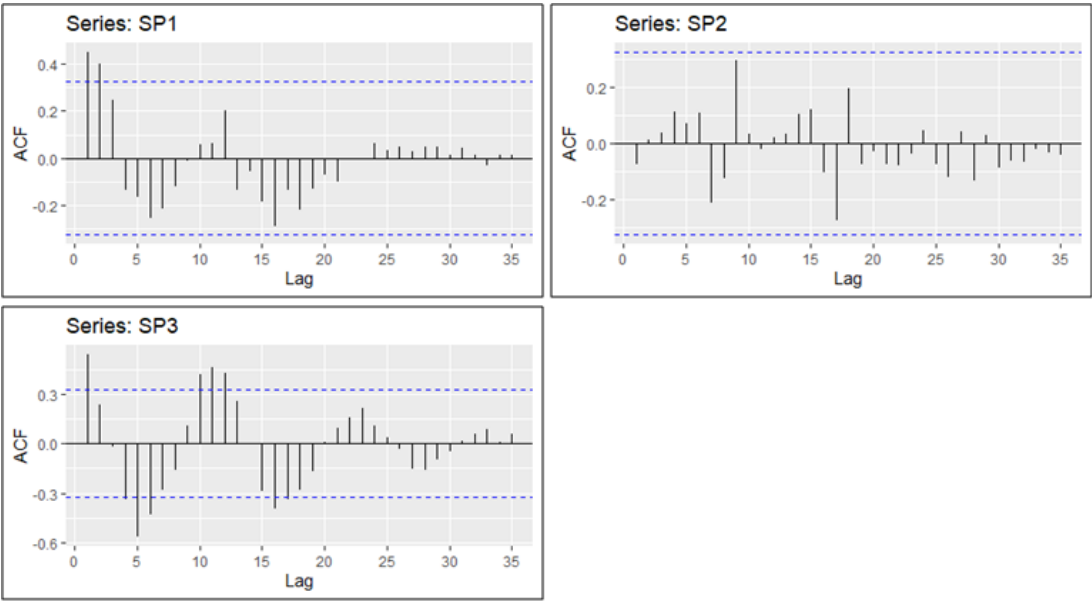


Figure 3.4 ACF plots of three spare parts

Seasonal pattern on the time plots and ACF plots of three spare parts is observed.

3.2.5. Current demand forecasting of the company

The company currently uses 12-month moving average of demand to estimate next month demand and maximum stock level. Time plots and ACF of three sample spare parts show a seasonal pattern. However, moving average method does not consider seasonal pattern on time series. Forecasting accuracy, maximum stock level, order quantity, stock on hand amount and lost sales amount of spare parts for last 12 months as test period will be calculated by using 36 months demand data of three sample spare parts. Their demand forecasts between 25th and 36th month will be calculated by using demand data between 13th and 35th month (Figure 3.5).

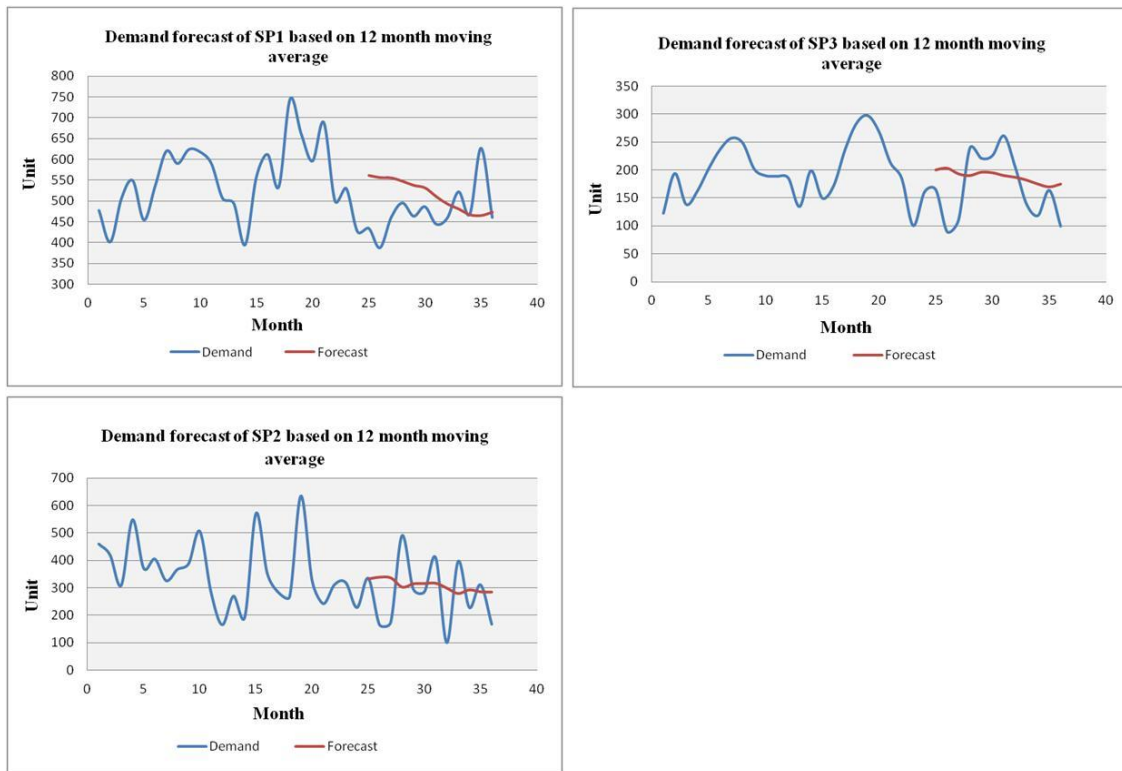


Figure 3.5 Demand forecasts of three sample spare parts by using 12-month moving average

3.2.5.1. Forecasting accuracy, stock on hand amount and lost sales amount

The reason to check stock on hand amount and lost sales amount at the same time is that measuring forecasting accuracy seems not enough to compare forecasting methods. Because, thousands of stock items are issued, financial results should also be

considered. A forecasting method can generate better result for low cost stock items while it may not generate good results for high cost stock items. Therefore, an overall approach is needed. Target value of stock on hand amount and lost sales amount is zero for all spare parts sales and procurement operations.

After obtaining forecast values of last 12-month and rounding to integer value, stock on hand amount and lost sales amount will be computed for each part as follows;

On hand stock occurs when summation of previous month stock quantity and order quantity is greater than demand quantity. On hand quantity is multiplied by unit part cost to get on hand amount.

On hand stock = previous month stock qty + order qty – demand qty

On hand amount = on hand stock x unit part cost

Lost sales occur when summation of previous month stock quantity and order quantity is lower than demand quantity. Lost sales quantity is multiplied by 50% of unit part cost to get lost sales amount. Company makes up sales price by adding 50% markup to unit cost price. If on hand stock does not meet demand, company loses profit. Company does not want to lose profit and does not want to keep stock more than needed.

Lost sales qty

$$= \begin{cases} \text{demand qty} - (\text{previous month stock qty} + \text{order qty}) & \text{if on hand stock is negative} \\ 0 & \text{otherwise} \end{cases}$$

Lost sales amount = lost sales quantity x (0.5 x unit part cost)

The company compensates stock shortage and lost sales by borrowing part from sub dealers or cannibalizing main product. In reality, it meets customer demand with very high cost and unwanted supply methods.

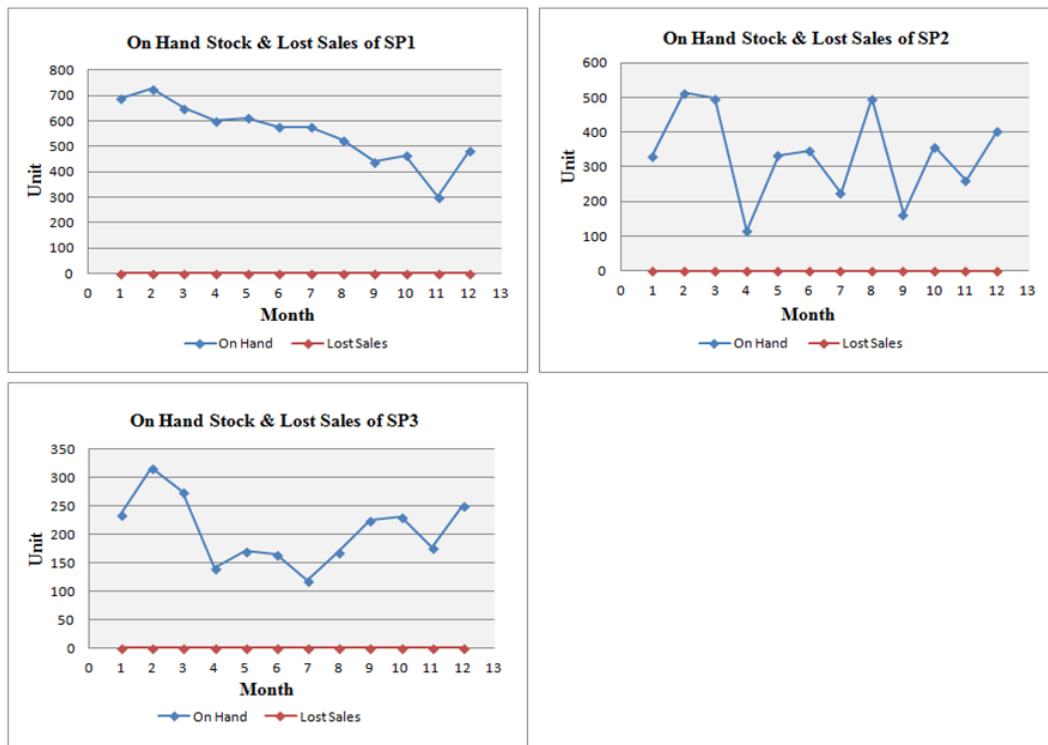


Figure 3.6 On Hand Stock & Lost Sales Quantity for test period with 12-month moving average

Table 3.3 shows MSE, on hand stock amount and lost sales amount of three spare parts for last 12-month test period after demand forecast calculation with moving average.

Table 3.3 MSE, On Hand Stock Amount and Lost Sales Amount with 12- month moving average

	MSE	On Hand Amount (€)	Lost Sales Amount (€)
SP1	8.233	266.440	0
SP2	14.441	161.880	0
SP3	3.393	98.880	0

On hand stock amount and lost sales amount are not direct costs but they create negative impact on financial status of the company. Because, they are costly and unwanted values, an objective function (OF) can be developed by combining them to have an overall financial approach for whole inventory. Aim of the demand forecasting should be minimizing these amounts and making the total of them close to ideal value zero.

$$\text{Min. OF} = \text{On Hand Amount} + \text{Lost Sales Amount}$$

If the values on Table 3.3 considered, OF will be;

$$OF = 527.200 + 0 = 527.200 \text{ Euro}$$

The aim of this study is to reduce this amount by using Holt-Winters` and ARIMA forecasting methods for the same test period.

3.2.6. Demand forecasting with Holt-Winters` method

There are two different Holt-Winters' methods; additive or multiplicative type. This classification is based on exponential or linear behavior of forecast variable. In this case, spare parts demand is the variable. When time plot of three spare parts are analyzed, it is difficult to determine additive or multiplicative seasonal pattern. Therefore, demand forecast of three parts will be calculated by using additive and multiplicative Holt-Winters' methods. Afterwards, MSE, on hand stock amount and lost sales amount will be computed.

3.2.6.1. Additive method

After initialization values were determined, last 12 month demand forecast of three sample spare parts were calculated by using Holt-Winters' additive method (Figure 3.7). Initial smoothing parameters were 0.2 for α , β and γ . Errors and MSE values were computed for last 12 months. However, smoothing parameters can get value between 0 and 1. Different combinations between 0 and 1 can reduce MSE. Forecasting accuracy can be improved by optimizing smoothing parameters (Makridakis et al., 1998). MS Excel Solver was used to optimize smoothing parameters to minimize MSE value. MSE values reduced from 4.907 to 3.069 for SP1, from 15.552 to 10.463 for SP2 and from 2.791 to 2.374 for SP3. New smoothing parameters became $\alpha = 0.577$, $\beta = 0$ and $\gamma = 1$ for SP1, $\alpha = 0$, $\beta = 0.132$ and $\gamma = 0.353$ for SP2 and $\alpha = 0.041$, $\beta = 1$ and $\gamma = 0.172$ for SP3 after optimization.

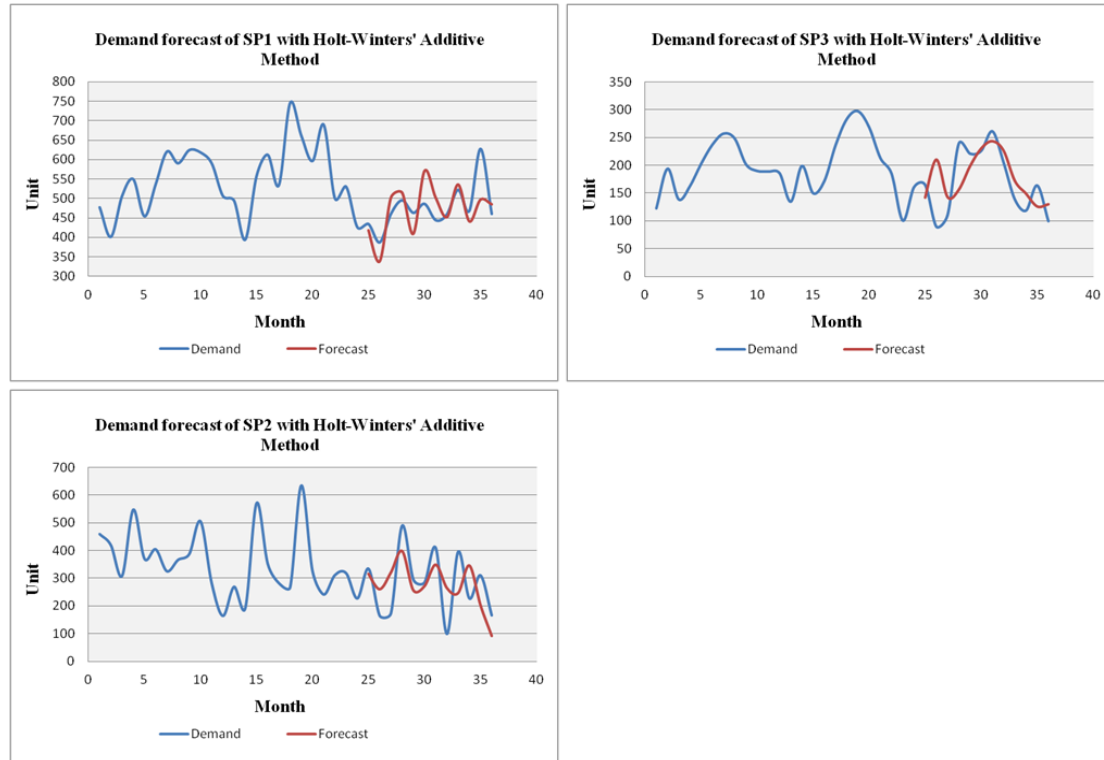


Figure 3.7 Demand forecasts of three sample spare parts by using Holt-Winters' additive method

Table 3.4 shows MSE, on hand stock amount and lost sales amount of three spare parts for last 12-month test period after demand forecast calculation with Holt-Winters' additive method.

Table 3.4 MSE, On Hand Stock Amount and Lost Sales Amount with Holt-Winters' additive method

	MSE	On Hand Amount (€)	Lost Sales Amount (€)
SP1	3.069	225.080	0
SP2	10.463	131.960	0
SP3	2.374	88.400	0

Objective function can be calculated to see overall effect by using values on Table 3.4 after obtaining on hand amount and lost sales amount for three spare parts with Holt-Winters' additive method (Figure 3.8).

Min. OF = On Hand Amount + Lost Sales Amount

OF = 445.440 + 0 = 445.440 Euro

Total of on hand amount and lost sales amount decreased by almost 15.5% comparing to moving average method.

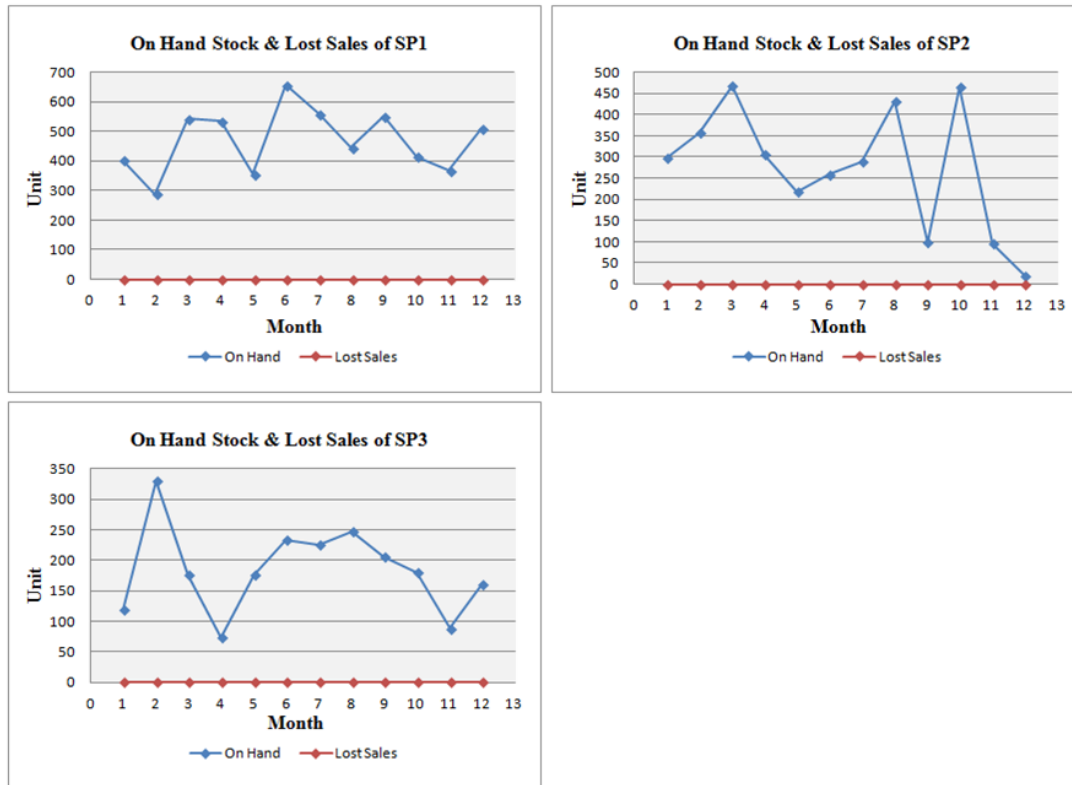


Figure 3.8 On Hand Stock & Lost Sales Quantity for test period with Holt-Winters' additive method

3.2.6.2. Multiplicative method

Last 12 months demand forecasts of three sample spare parts were calculated by using Holt-Winters' multiplicative method after initialization values were determined (Figure 3.9). Initial smoothing parameters were 0.2 for α , β and γ . Errors and MSE values were computed for last 12 months. MS Excel Solver was used to optimize smoothing parameters to minimize MSE values. MSE values reduced from 4.441 to 2.563 for SP1, from 16.015 to 9.910 for SP2 and from 2.811 to 2.398 for SP3. New smoothing parameters became $\alpha = 0.538$, $\beta = 0$ and $\gamma = 1$ for SP1, $\alpha = 0.001$, $\beta = 1$ and $\gamma = 0.284$ for SP2 and $\alpha = 0.039$, $\beta = 1$ and $\gamma = 0.348$ for SP3 after optimization.

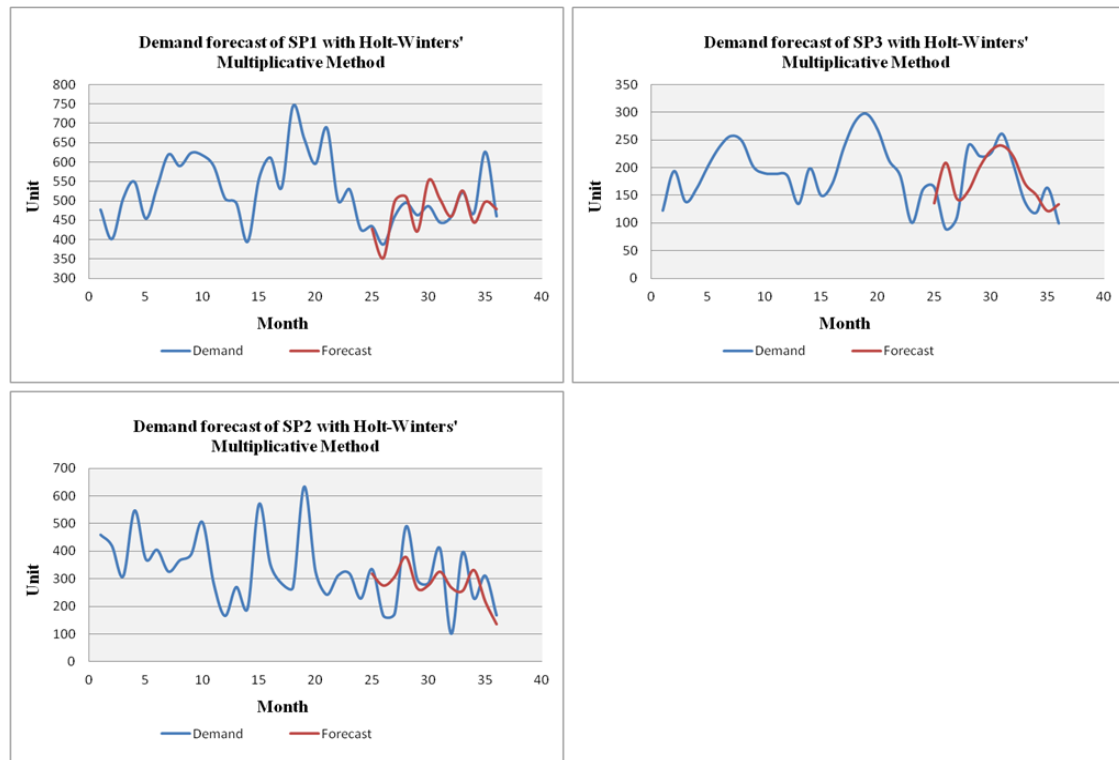


Figure 3.9 Demand forecasts of three sample spare parts by using Holt-Winters' multiplicative method

Table 3.5 shows MSE, on hand stock amount and lost sales amount of three spare parts for last 12-month test period after demand forecast calculation with Holt-Winters' multiplicative method.

Table 3.5 MSE, On Hand Stock Amount and Lost Sales Amount Holt-Winters' multiplicative method

	MSE	On Hand Amount (€)	Lost Sales Amount (€)
SP1	2.563	226.040	0
SP2	9.910	135.000	0
SP3	2.398	87.840	0

Objective function can be calculated to see overall effect by using values on Table 3.5 after obtaining on hand amount and lost sales amount for three spare parts with Holt-Winters' multiplicative method (Figure 3.10).

$$\text{Min. OF} = \text{On Hand Amount} + \text{Lost Sales Amount}$$

$$\text{OF} = 448.880 + 0 = 448.880 \text{ Euro}$$

Total of on hand amount and lost sales amount decreased by almost 14.9% comparing to moving average method.

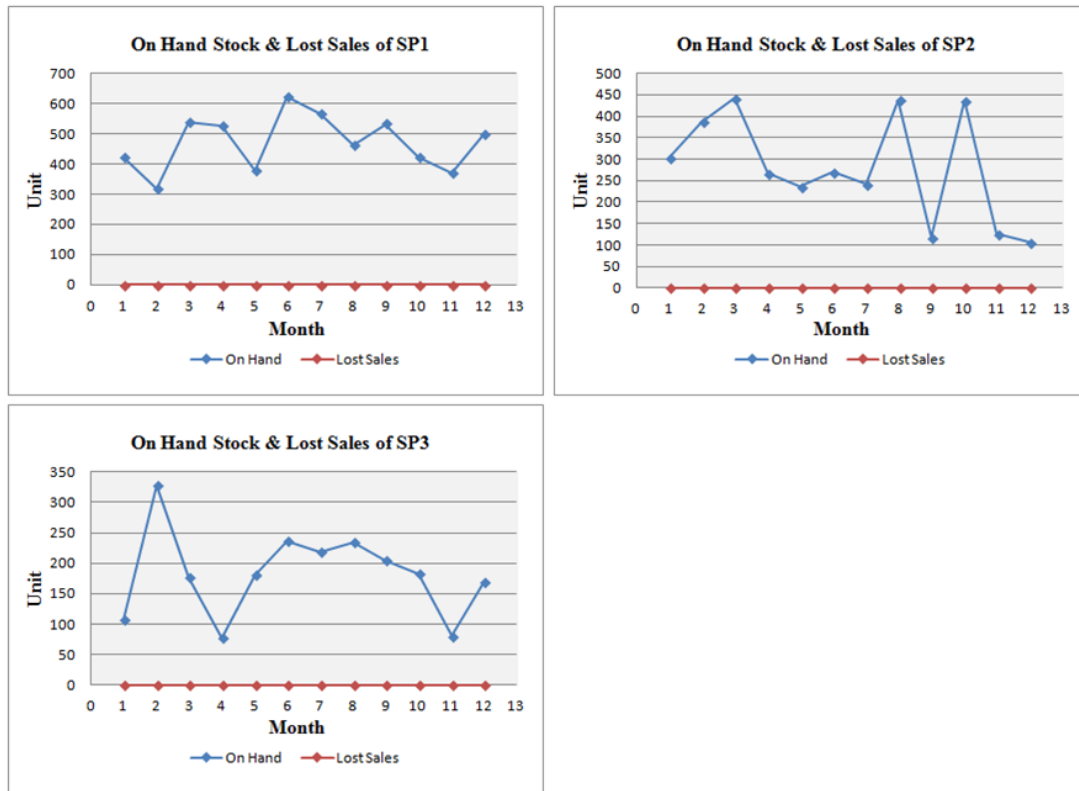


Figure 3.10 On Hand Stock & Lost Sales Quantity for test period with Holt-Winters' multiplicative method

3.2.7. Demand forecasting with ARIMA method

Demand data of three spare parts shows seasonal pattern. ARIMA gives better demand forecast result for seasonal pattern when demand data set is long enough. In this case, there are only 24 months demand data for seasonal ARIMA model fitting. Therefore, instead of using seasonal ARIMA model, non-seasonal ARIMA model will be preferred to get better result. Latest monthly demand data will be added to 24 months moving demand data and oldest monthly data will be dropped from the data set.

R software is used for calculations. Auto.arima function on R finds best ARIMA model. 12 data sets which include 24 months moving demand data prepared for three spare parts each and loaded to R. Auto.arima function analyzed first data set of each spare part and recommended (4,0,0) model for SP1, (0,0,0) model for SP2 and (1,0,0) for SP3. It is difficult to handle with different ARIMA models for inventory planners. Therefore, one ARIMA model should be selected among recommended models by R. All recommended ARIMA model combinations calculated for SP1, SP2 and SP3.

ARIMA(1,0,0) model provided minimum forecast accuracy and objective function value for 12 months (Figure 3.11).

Equation for ARIMA(1,0,0) model is:

$$Y_t = c + \phi_1 Y_{t-1} + e_t \quad (3.2)$$

Auto.arima function finds best ARIMA model and model parameters by calculating AICc value. Arima function fits ARIMA model to the data and forecast function generates forecast value for the next period by using model equation and parameters.

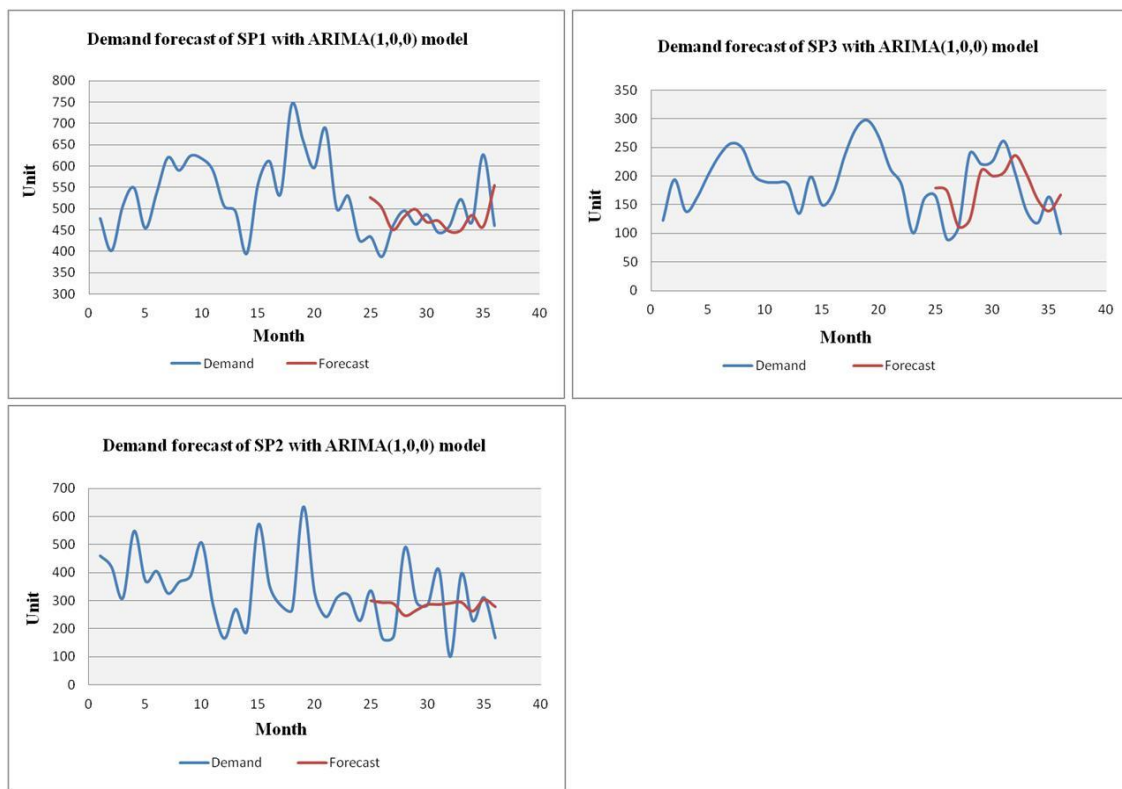


Figure 3.11 Demand forecasts of three sample spare parts by using with ARIMA(1,0,0) model

Table 3.6 shows MSE, on hand stock amount and lost sales amount of three spare parts for last 12-month test period after demand forecast calculation with ARIMA(1,0,0) model.

Table 3.6 MSE, On Hand Stock Amount and Lost Sales Amount with ARIMA(1,0,0) model

	MSE	On Hand Amount (€)	Lost Sales Amount (€)
SP1	5.694	235.560	0
SP2	13.934	138.200	0
SP3	3.001	86.960	0

Objective function can be calculated to see overall effect by using values on Table 3.6 after obtaining on hand amount and lost sales amount for three spare parts with ARIMA(1,0,0) model (Figure 3.12).

Min. OF = On Hand Amount + Lost Sales Amount

OF = 460.720 + 0 = 460.720 Euro

Total of on hand amount and lost sales amount decreased by almost 12.6% comparing to moving average method.

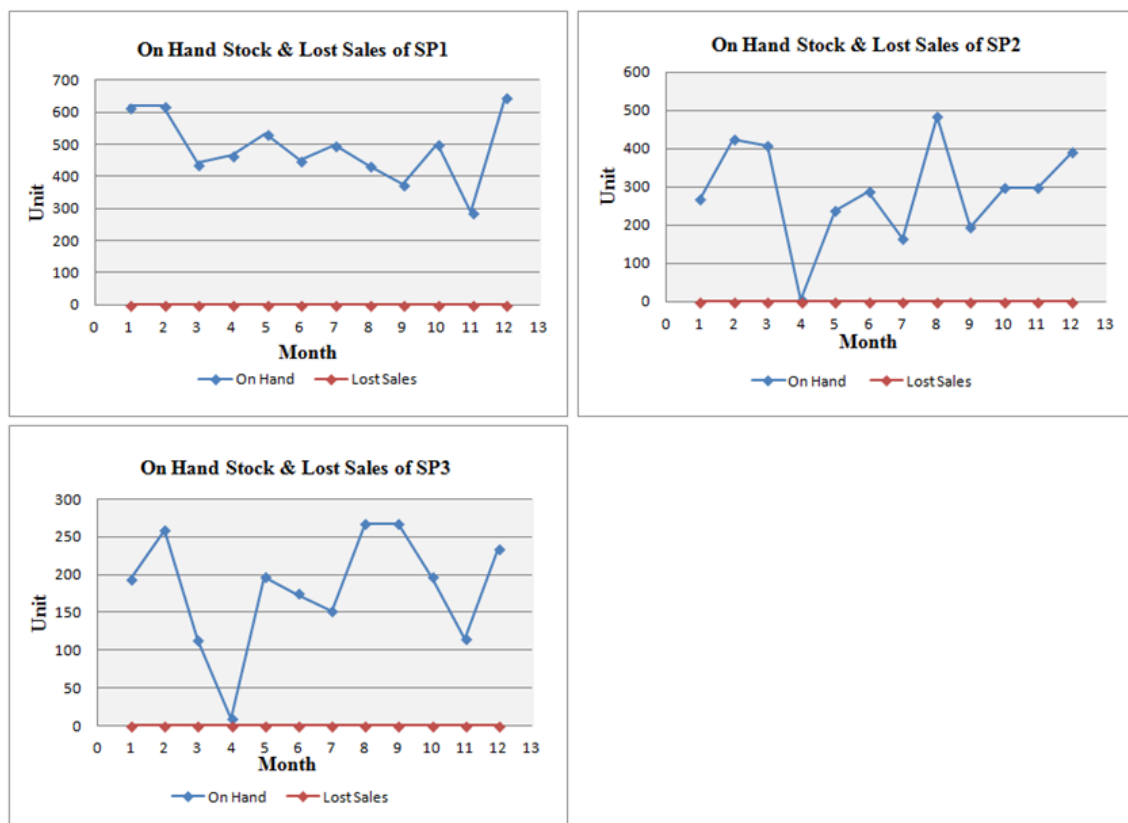


Figure 3.12 On Hand Stock & Lost Sales Quantity for test period with ARIMA(1,0,0) model

3.3. Result

Holt-Winters' methods and ARIMA models were used to calculate demand forecast of three spare parts for 12-month test period. MSE value, on hand amount, lost sales amount and total of on hand amount and lost sales amount obtained and results were compared to current forecasting method on Table 3.7.

Table 3.7 MSE, On Hand Stock Amount and Lost Sales Amount obtained by using different forecasting methods for three sample spare parts on test period

	Parts	MSE	Total MSE	On Hand Amount (€)	Total On Hand Amount (€)	Lost Sales Amount (€)	Total Lost Sales Amount (€)	Total On Hand & Lost Sales Amount (€)
Moving Average	SP1	8.233	26.067	266.440	527.200	0	0	527.200
	SP2	14.441		161.880		0		
	SP3	3.393		98.880		0		
Holt-Winters' Additive	SP1	3.069	15.905	225.080	445.440	0	0	445.440
	SP2	10.463		131.960		0		
	SP3	2.374		88.400		0		
Holt-Winters' Multiplicative	SP1	2.563	14.871	226.040	448.880	0	0	448.880
	SP2	9.910		135.000		0		
	SP3	2.398		87.840		0		
ARIMA(1,0,0)	SP1	5.694	22.629	235.560	460.720	0	0	460.720
	SP2	13.934		138.200		0		
	SP3	3.001		86.960		0		

Alternative forecasting methods did not cause any lost sales quantity and amount despite decrease in on hand amount. Holt-Winters' Additive method provided 38.98% decrease in MSE, 15.51% decrease in on hand amount and in total of on hand & lost sales amount comparing to current forecasting method moving average.

Holt-Winters' Multiplicative method provided 42.95% decrease in MSE, 14.86% decrease in on hand amount and in total of on hand & lost sales amount comparing to current forecasting method moving average.

ARIMA(1,0,0) model provided 13.19% decrease in MSE, 12.61% decrease in on hand amount and in total of on hand & lost sales amount comparing to current forecasting method moving average.

As a result, Holt-Winters' Additive method provided the most accurate demand forecast of three spare parts for 12-month test period. It also provided lowest on hand amount and objective function.

4. CONCLUSION

Considering thousands of stock items and millions of US dollars inventory investment, demand forecast with Holt-Winters' Additive method makes significant improvement for the company. Therefore, the company will be advised to use Holt-Winters' Additive method and to make similar studies periodically in the future.

The study presents an application for companies to see benefits of quantitative forecasting techniques. It explains step by step how to deal with uncertain and variable demand, importance of finding out type of pattern on the demand data, determining appropriate forecasting method based on data pattern, and forecasting future values. The study takes into account minimization of on hand stock amount and lost sales amount, hence provides an approach to reduce the cost of spare parts.

For further research, beside demand forecasting methods, inventory classification techniques such as ABC analysis or VED analysis (Vital, Essential, and Desirable) are very important for inventory cost minimization studies. These classification techniques provide a systemic analysis on inventory. Safety stock should be added ordering calculations if there are any lost sales or service level concerns.

Also, demand forecasting software can be developed and integrated to an ERP system with an interface. Thus, forecasting software can get historical demand data automatically and sends back forecast values to ERP system.

Companies invest millions of US dollars in their inventory to make profit and to meet customer demands. Therefore, any improvement on inventory cost provides financial benefits to companies and increases customer satisfaction.

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RESUME

ALPER SADIK TAVUKÇU

EDUCATION

2018 - 2021 Marmara University

M.Sc. in Industrial Engineering

1994-1998 Istanbul University

B.Sc. in Industrial Engineering

WORK EXPERIENCE

2016 – 2018 Maats Is Makinalari (Doosan Distributor)

Spare Parts Procurement & Logistics Executive

2008 – 2015 Temsa Is Makinalari (Komatsu Distributor)

Dealer Network Executive

Spare Parts Sales & Procurement Executive

Spare Parts Purchasing & Procurement Engineer

2005 - 2006 Anadolu Isuzu Automotive Industries

Production Planning Engineer

2002- 2004 Efe Automotive Industries

Production & Planning Engineer

1998 – 1999 Pinar Food Industries

SAP Junior Specialist